The Primary Advantage in Utilizing Remote Sensing Assets for Extreme Heat Vulnerability Studies

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Remotely sensed imagery provides an alternate view of spatial characteristics that in situ measurements typically lack. This is an advantage to utilizing such datasets for the analysis of environmental health vulnerabilities.

Data acquired with remote sensing instruments from Earth observation systems have been used in a variety of environmental health applications (Kelly et al. 2011, Bergquist 2011, Bergquist and Rinaldi 2010, Rochon et al. 2010). Much of the corpus of this research deals with vector-borne disease and the associated habitat, which is readily observable and quantifiable from satellite and aerial platforms. Air quality assessments and examinations also are present in the literature linking health effects of air pollution to aerosol optical depth (AOD), nitrous oxides, or other components that are observable remotely (Guo et al. 2011, Bridhikitti and Overcamp 2011, van Pinxteren et al. 2010, Hu, Sokhi and Fisher 2009; Liu, Paciorek and Koutrakis 2009). Satellite remote sensing data have been utilized to examine the health effects of extreme heat events and the related urban heat island effect (Uejio et al. 2011, Dousset et al. 2011; Stone, Hess and Frumkin 2010; Johnson and Wilson 2009). There is a central advantage to utilizing remote sensing in heat-related health studies that has not been brought to the forefront of discussion. This advantage is related to the unique nature of remotely sensed data when compared to the related in situ measurements often sampled and used for spatial interpolative purposes.

As most researchers that exploit remote sensing data are aware, the information collected is done so in a relatively systematic fashion. For example, a LandSAT 8 image is captured in a nearly instantaneous manner. The typical size of a LandSAT scene is 198 kilometers by 180 kilometers, which equates to 6,600 samples by 6,000 samples integrally related to the spatial resolution of 30 meters. If one were to collect in situ measurements of the same observable phenomena it would be an impossible task; certainly impossible to do so instantaneously. In addition to the impractical nature of comparing field collection of the same values, there would likely be the introduction of bias into the sampling design that is inherently absent in the remote sensing approach. This is certainly not to say that remote sensing does not have limitations, which it certainly does, but is shown simply to make the point that for certain health-related uses, especially given the context of extreme heat vulnerability studies, remote sensing provides a level of awareness that is lacking in field-based temperature assessments. This knowledge provides health professionals, emergency management agencies, and if provided to them – the general public – with information regarding the distribution of heat within the given location.

Clearly, the most important information that is necessary to declare a heat emergency for a specific location is the temperature. One method of doing so is to examine the percentile of temperature over a certain range of time and compare it to the forecast high temperature over the forthcoming days. Typically, if one is to expect a temperature that exceeds the 95th percentile for a series of five days and/or the 97th percentile for three days, then an extreme heat threshold is surpassed (Robinson 2001). However, the basis for this declaration is typically done by an in situ measurement of the air temperature at a single location collected within the confines of a standardized network of surface-based thermometers. As extreme heat conditions begin to develop, one is likely to see the previously mentioned thresholds exceeded in different areas at different times. That is to say, the spatial and temporal distribution of heat within an urban area will be anisotropic (i.e., vary in different directions) depending on land cover characteristics. This is demonstrated by the urban heat island effect and the related micro-urban heat islands observable by satellite technologies (Aniello et al. 1995).

For example, a city may not be expecting extreme heat thresholds to be surpassed for several days and the forecasted extreme heat warning is not to be declared for two additional days. This forecast is based on the National Weather Service network and does not take into account the spatial variations that are visualized in a remotely sensed image. By utilizing a remotely sensed thermal image to drive decision-support during extreme heat events, one would have a significantly enhanced level of spatial specificity when attempting to drive response efforts. These efforts could either be planned in advance or conducted concurrently with an ongoing extreme heat event. Figure 1 shows a one-year time series of thermal satellite data for Indianapolis, Indiana, showing the different temperature percentiles exceeded (Johnson et al., 2013). The only time where an extreme heat warning was issued was in the June 29 image. However, thresholds were exceeded in other areas of the city on days where no heat warning was issued. This has obvious implications for planning and emergency management and would have been missed by only relying on the official temperature for the city. More research needs to be conducted on these areas of elevated temperature to determine their relevance to vulnerability and to develop more robust spatiotemporal models (cf: Johnson et al., 2013).

There are certainly caveats that need to be recognized when comparing the temperatures captured through the in situ techniques and those collected with remote sensing instruments. The field-based thermometer is measuring the ambient air temperature where the remote sensing technique is at best capturing the land surface temperature (LST). Local conditions can dictate the difference between the two, but in some cases they can be fairly significant. LST does contribute to the ambient air temperature, which is demonstrated in the daily diurnal temperature cycle, however care should be exercised and the difference between the two needs to be specified and understood. The spatial distribution of the LST especially as it relates to socioeconomic conditions provides an improving understanding and depiction of extreme heat vulnerability (Johnson, Wilson and Luber 2009, Harlan et al. 2006).

Advances need to be made in the collection of satellite-based thermal data, especially in relation to the spatial and temporal resolution of acquisition. Currently, the Moderate Resolution Imaging

Spectroradiometer (MODIS) and Visible Infrared Imaging Radiometer Suite (VIIRS) in the Earth Observation Constellation collect thermal data on a daily basis. This is a satisfactory temporal resolution but the spatial resolution of 1 kilometer and 750 meters, respectively, is inadequate for the examination of local-scale variations. The downscaled 30-meter resolution of the LandSAT series is sufficient for local-scale spatial variations but inadequate in its temporal resolution of ~16 days. Figure 2 demonstrates the difference in the spatial resolution of the MODIS and Landsat series of satellites. Clearly, the MODIS image provides a more strategic view of the area. The Landsat image is more tactical in its ability to visualize finer patterns of spatial heterogeneity. A multi-sensor fusion framework might be a likely area of further development and refinement of the available data (Meng, Borders and Madden 2010, Dong et al. 2009, Koetz et al. 2008). This approach could have the potential to support decision-making during the temporal context of the heat event (daily or more frequent forecasting and guidance) and the spatial context of vulnerability assessment.

As demonstrated by this short narrative and previous research, remotely sensed imagery provides an alternate view of spatial characteristics that in situ measurements typically lack. This is certainly an advantage to utilizing such datasets for the analysis of environmental health vulnerabilities. As new sensors, algorithms, and techniques are developed it is anticipated that researchers and public health professionals will further exploit the usefulness and availability of such datasets.

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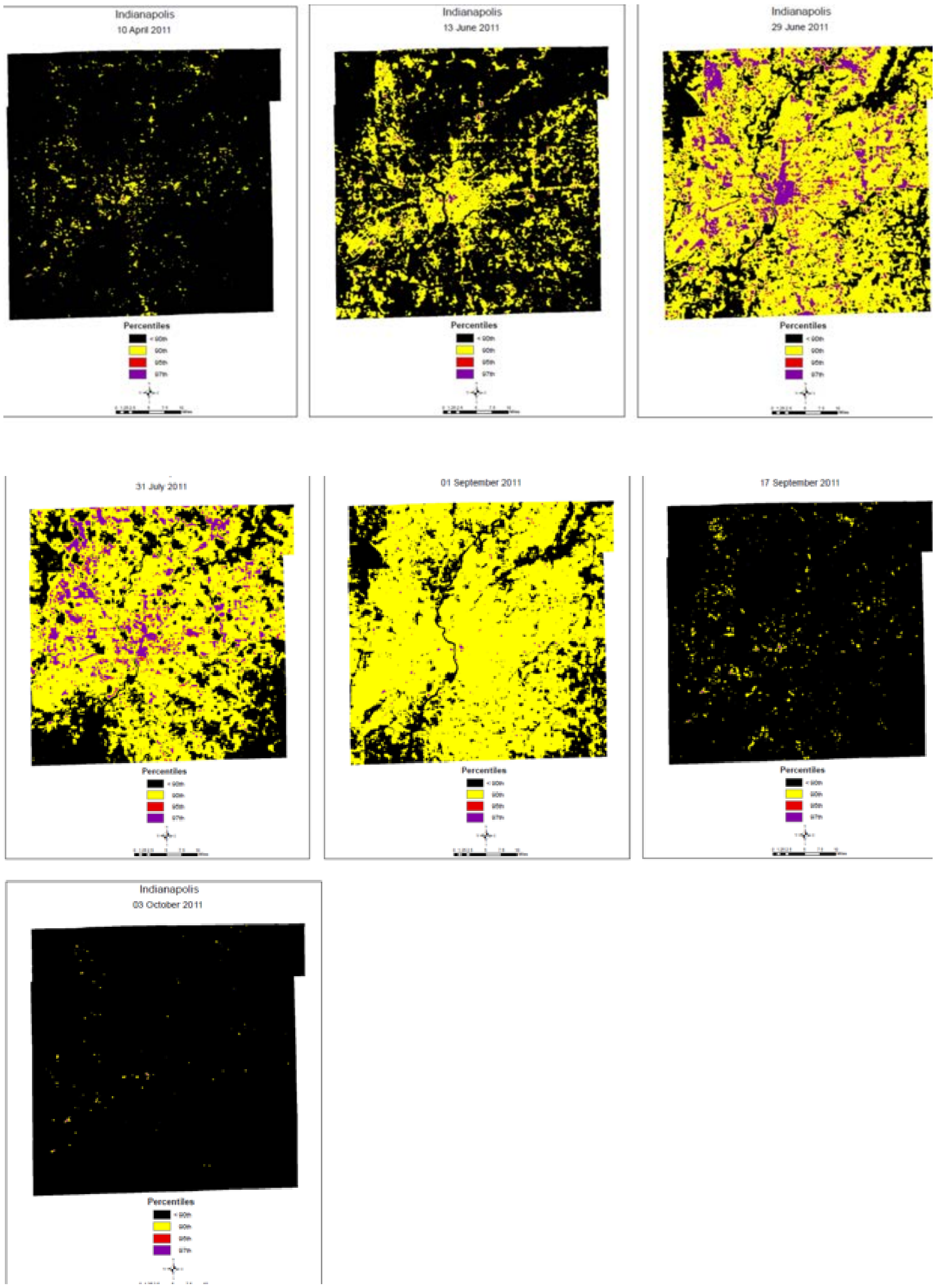

Figure 1: Percentile (ambient temperature) thresholds exceeded during 2011 in Indianapolis, Indiana (Only June 29, 2011, was a declared extreme heat event day). Image Credit: Johnson et al., 2013.

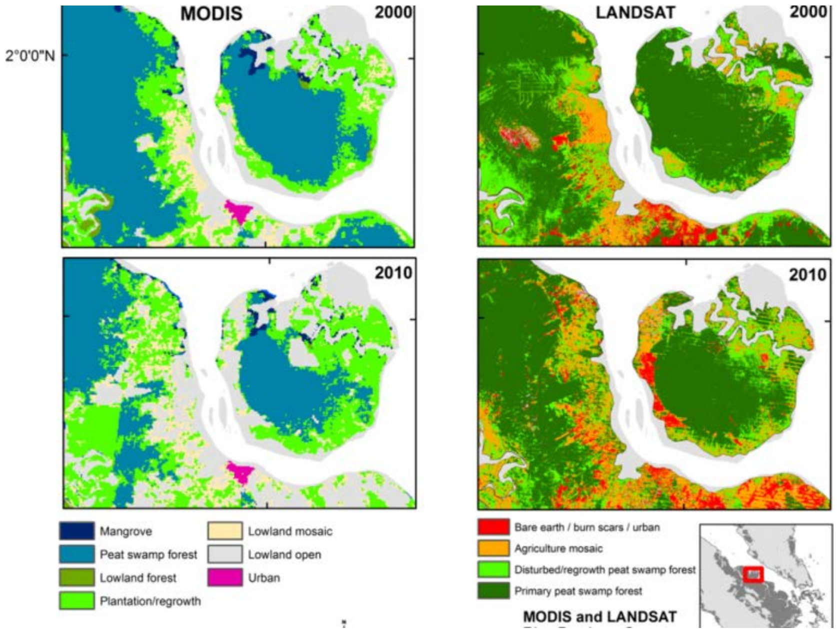

Figure 2: This example from a previous study concerning peat bog classification demonstrates the difference in the spatial resolution of MODIS compared to Landsat. Notice the pixels in the images on the left are much larger than those on the right. Image Credit: Wijedasa et al., 2012.